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Substitution between Foreign Capital in China, India, the Rest of the World, and Latin America:

Much Ado about Nothing?

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Abstract

This paper explores the impact of the emergence of China and India on foreign capital stocks in other economies. Using bilateral data from 1990-2003 and drawing from the knowledge-capital model of the multinational enterprises to control for fundamental determinants of foreign capital stocks across countries, the evidence suggests that the impact of foreign capital in China and India on other countries' foreign capital stocks has been positive. This finding is robust to the use of ordinary least squares, Poisson, and negative binomial estimators; to the inclusion of time and country-pair fixed effects; to the inclusion of natural-resource endowments; and to the use of the sum of foreign capital stocks in Hong Kong (China) and mainland China instead of using only the latter's foreign capital stocks. There is surprisingly weak evidence of substitution in manufacturing foreign capital stocks away from Central America and Mexico in favor of China, and from the Southern Cone countries to India, but these findings are not robust to the use of alternative estimation techniques.

This paper—a product of the Office of the Chief Economist for Latin America and the Caribbean—is part of a larger effort in the department to understand the effects of the growth of China and India on Latin Ameircan and Caribbean economies. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The author may be contacted at dlederman@worldbank.org.

Substitution between Foreign Capital in China, India, the Rest of the World, and Latin America: Much Ado about Nothing?

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1. Introduction

There is an increasing concern in developing countries about competition from China and India in the attraction of foreign direct investment (FDI). The outstanding economic growth, together with the large populations and low wages in these emerging economies make them particularly attractive to foreign investors. In fact, China and India were ranked the two most attractive global business locations by transnational companies in UNCTAD's survey of FDI prospects. [1]

The emergence of China and India as potential competitors for FDI, together with a slowdown in FDI inflows to other developing countries at the beginning of the 21st century raised the alarm. For many, the relocation of production facilities from, for example, Latin America and the Caribbean (LAC) to China and India has already begun. The World Investment Directory claims that "…[the] relocation of the maquila industry was largely, but not exclusively, due to fiercer competition from Asia", when referring to the slowdown in Mexico's FDI inflows. [2]

A first look at the data reveals that foreign capital stocks (FCS) have become increasingly important in developing countries, including LAC, during the past 15 years. By 2004, aggregate stocks in LAC reached $600 billion dollars, about six times more than in 1990. [3] More than 80 percent of these stocks are concentrated in five countries, namely Argentina, Brazil, Chile, Mexico, and Venezuela. Over the same period, FCS in China grew at an even faster speed, from $20 billion in 1990 to $245 billion in 2004, the

[1] UNCTAD (2005) FDI prospects survey.
[2] UNCTAD (2004).
[3] UNCTAD, Foreign Direct Investment Database (www.unctad.org). We do not include Bermuda, Cayman Islands and Virgin Islands in the Latin American figures as part of LAC.

largest FCS in the developing world. FCS in India increased from $1.6 to almost $40 billion during the same period.

The sources of foreign capital in developing countries differ from one region to another. A study by the Inter-American Development Bank (IDB 2005) reveals that FDI sources are different for China than for LAC. For this reason, it is perhaps more interesting to understand the evolution of FCS from OECD countries, which comprise about 68 percent of total stocks into Latin America. China and particularly India are still far from the levels of FCS found in the major LAC economies from these sources. Mexico had almost twice as much capital from the OECD than China by 2003, and almost seven times more than India. OECD stocks in China and India grew faster than in LAC during 1990-2003. This trend is less clear for the 1997-2003 period, especially for China. In fact, relative to GDP growth, FCS grew more in LAC countries than in China since 1997 (Cravino, Lederman, and Olarreaga 2006).

The effect of FCS in China and India on other economies is theoretically ambiguous, however. For China and India to have a negative effect on others, global FDI supply would have to be inelastic, as well as globally integrated so that competition for FDI becomes a zero-sum game. Furthermore, as noted by Eichengreen and Tong (2005), if production processes are vertically integrated across countries, increasing production in China or India would require increasing production in other locations. Therefore, empirical work is needed to ascertain whether the growth of China and India have been complements or substitutes for foreign capital in alternative locations.

We estimate these effects drawing on the "Knowledge-Capital Model" (KCM). We augment this model with Chinese and Indian Foreign Capital Stocks (FCS) and interactions of these variables with a dummy for LAC economies to test for heterogenous effects across different groups of developing countries. We also test the robustness of the KCM to the inclusion of proxies concerning the relative abundance of natural resources.

We find that there is no substitution effect between FCS in China and India and those in LAC or other hosts of FCS. When using sector-level FCS data from the U.S., we continue to find that there is no robust substitution effect from China or India on manufacturing-sector FCS in other countries, including LAC and Central America and Mexico. In some cases we cannot reject the hypothesis of no substitution effect of Chinese FCS on Central America and Mexico or of Indian FCS on FCS in the Southern Cone countries of LAC. But these results are not robust across econometric techniques. In fact, to our knowledge, this is the first study of determinants of foreign capital across countries that utilizes OLS as well as count-data estimators (Poisson and Negative Binomials), which are consistent in the presence of systematic heteroskedasticity that might render OLS and other linear estimators unreliable.

The rest of the paper is organized as follows. The next section reviews related literature. Sections 3 and 4 describe the methodology and data. Section 5 presents and discusses the econometric results. The last section concludes.

2. Related Literature

There is a recent literature that estimates econometrically the impact of China's emergence as a large host of foreign capital on the developing world. Chantasasawat et al. (2004) use data on aggregate FDI inflows for a group of Asian and Latin American countries. After controlling for other FDI determinants, they find that China's FDI is positively correlated with inflows to East and Southeast Asia and insignificantly correlated with FDI to Latin America. In contrast, Marcereau (2005) finds a substitution effect between China and other Asian countries, although this effect is driven by two countries, Singapore and Myanmar. Garcia-Herrero and Santabarbara (2005) use bilateral data on FDI among source-host country pairs during 1984-2001 and do not find a substitution effect between Chinese and Latin American FDI. However, they do find a negative relationship between China and Latin American inflows when they focus on 1995-2001, especially for Mexico and Colombia. Eichengreen and Tong (2005) use a "gravity model" of bilateral FDI that controls for both countries' GDPs, GDP per capita, and other variables used in the standard trade gravity model, such as distance and common language. They then augment this model with China's FDI inflows, and find that China has a positive effect on inflows to others developing countries but no effect on Latin America.

There is a gap in the literature when it comes to estimating the impact of India on foreign investment in other economies. This is one of the contributions of this paper.

We follow Eichengreen and Tong (E.T.) by including FCS in China and India in FCS regressions using bilateral FCS data collected by OECD and UNCTAD. One potential pitfall of ET, however, is their use of the gravity model, which is not grounded in FDI theory. We draw on an alternative specification, namely the "Knowledge-Capital Model" (KCM), which is grounded on the theory of the multinational enterprise and has been estimated in recent papers by Carr, Maskus and Markusen (2001), Blonigen, Head and Davis (2003), and Blonigen and Davies (2002). We augment the KCM with Chinese and Indian FCS and interactions of these variables with a dummy for LAC countries. A negative coefficient on these variables would then indicate that FCS in China or India is growing at the expense of FCS in other regions. As will become clear later, the standard empirical versions of the KCM in the literature have ignored the potential role of natural resources as drivers of international investment. Hence we also test the robustness of the augmented KCM model to the inclusion of empirical proxies that capture the relative abundance of natural resources in host countries.

Another challenge for the existing literature is the commonplace assumption that the effect of China is homogeneous across sectors. In fact, the available data from the U.S. foreign capital abroad indicates that the evolution of manufacturing-sector FCS across countries has been different than the trends of aggregate FCS (Cravino, Lederman, and Olarreaga 2006). The manufacturing sector seems particularly sensitive to relocation of multinationals into China and India as they search for lower labor costs. Thus, we take an additional step and estimate the effects of China and India on manufacturing-sector FCS in other countries, based on data on outward FCS from the U.S. We use a similar specification to the one with the aggregate data, which allows for different coefficients across host regions within the manufacturing sector.

Yet another concern about the existing literature is the exclusive application of OLS or other linear estimators to empirical models of the determinants of FDI or FCS. In the context of the gravity model of international trade, it is now known that such linear estimators can yield inconsistent coefficients due to the correlation between the expected value of bilateral trade flows among country pairs and the variance of their regression errors. This systematic heteroskedasticity produces log-linear estimates that are driven by the disproportionate influence of observations with high expected bilateral trade flows.

Indeed, Monte Carlo simulations suggest that the application of log-linear estimators to this type of data-generation process tends to produce substantial biases in the coefficients compared to the Poisson estimator, which controls for a constant correlation between the conditional mean of each observation and its regression-error variance (Santos Silva and Tenreyro 2005). Furthermore, if the data-generation process is characterized by over-dispersion (a rising ratio of variance over conditional mean) then the Negative Binomial estimator could be preferable. The data on bilateral FCS seems to be characterized by the same type of systematic heteroskedasticity that afflicts bilateral trade data, and consequently we subject all of our empirical models to the three estimators, namely OLS, Poisson, and Negative Binomials. Santos Silva and Tenreyro argue that the Negative Binomial estimator might not be desirable if the smaller observations are more prone to measurement errors than the larger observations.[4] To some extent, the use of outward FCS reported mainly by OECD countries might help deal with this concern, but to err on the side of caution, we report results from all three estimators. The following sections discuss the empirical models and the corresponding data.

3. Modeling the Determinants of FCS across Countries

Our approach is similar to the one proposed by ET, which is to utilize bilateral FCS in China and India in estimations of the determinants of FCS around the world. However, we use the KCM instead of the gravity model as a benchmark for our regressions, since it is grounded in formal FDI theory (Carr, Markusen, and Maskus 2001). This model allows for both horizontal and vertical motivations for FDI and was estimated in a number of

[4] Santos Silva and Tenreyro (2005) warn against estimating models were V[y/x] is a function of higher powers of E[y/x] when dealing with trade data. These models might give excessive weight to observations with low trade values, which may be ridden with measurement errors. This observation is less valid for our outward FCS data, since it is collected by OECD countries.

recent papers, including Carr, Markusen, and Maskus (2001); Blonigen, Davies, and Head (2003); and Blonigen and Davies (2004).

As noted by Blonigen and Head, one problem with FDI data is that it is highly skewed. Table A.1 in the appendix shows that the standard deviation in our dependent variable is about five times its mean. We therefore follow their specification throughout the paper, and estimate the model in logs[5]. Our benchmark regression is then:

$$FCS_{ijt} = f(SUMGDP_{ijt}, GDPDIFSQ_{ij,t,}, SKDIFF_{ijt}, SKDIFF\_NEG_{ijt}, F\_COST_{jt}, T\_COST_{it,} T\_COST_{jt,} DIST_{ijt}, \\ FCS_{iChinat}, FCS\_LAC_{iChinat}. FCS_{iIndiat}, FCS\_LAC_{iIndiat})$$

The first independent variable, SUMGDP, refers to the sum of source-country and host-country GDPs and is a measure of total market size. According to the KCM, the coefficient on this variable should be positive, since larger markets should attract multinational enterprises. This variable is thus expected to capture the horizontal motivation for FDI. GDPDIFSQ is the square of the difference of the two countries' GDP. The KCM predicts that, controlling for GDPSUM, differences in country size discourage horizontal FDI. The intuition is that when one of the countries is small, multinational firms would open production facilities mostly in the larger economy, and thus a negative sign on the coefficient of GDPDIFSQ captures this effect (when also controlling for SUMGDP) **.**

The next two terms in the equation capture the vertical motives of FDI. SKDIFF refers to the skill difference between the source and the host country. Theory predicts a positive coefficient on this variable, since differences in skill should proxy for differences in wages, which encourage MNCs to vertically integrate their production with economies

[5] There is nothing wrong with estimating the model in logs, since the theory does not provide an equation for the KCM.

where labor is less costly. However, empirical evidence on the impact of relative skill abundance is mixed. Blonigen, Davies and Head (BDH) and Maskus and Markusen (1999) found negative coefficients on this variable, indicating that FDI may seek high-skill labor. As noted in BDH, there is also a methodological issue about the interpretation of this variable. When the skill difference is positive (the source country is more skill abundant than the host country), an increase in this variable indicates that the difference in the skills in these countries is rising. In contrast, if the skill difference is negative, an increase in this variable indicates that the countries are becoming more alike. To deal with this issue, we follow BDH and take the absolute value of the skill difference. We then interact this variable with a dummy indicating when the skill difference is negative, to allow for a different coefficient when the host country is relatively more abundant in skilled labor.

The next four terms in the equation capture investment and trade costs. F_COST is the cost of investing in the host country, which is expected to have a negative effect on FCS. T_Costs capture the trade costs in the source and host countries. In the source country, trade costs should discourage vertical integration FDI by making production abroad less attractive as the costs of exports sent back to the source country reduce firm profits. In contrast, trade costs in the host country favor horizontal FDI to serve the host market (e.g. tariff-jumping FDI). DIST is the distance between countries. Since geographic distance among source and host economies affects trade and investment costs, its theoretical effect on FDI is ambiguous. Previous empirical studies found a negative coefficient on this variable (Carr et al 2001, Blonigen et al 2003).

The last terms of the equation are the variables of interest, and capture the impact of China and India on other economies' FCS. We also include an interaction with a dummy for LAC, since the impact on this region may differ from the world average.

FCS data contain negative and zero values, which might be a problem for the log-linear estimations. We deal with this issue in two ways. First, we follow Blonigen and Davies (2004) and truncate these observations to 0.1. Second, we use a Poisson pseudo maximum likelihood estimator. As discussed above, this approach proposed by Santos Silva and Tenreyro (2005) has the advantage of not requiring any transformation of the zeros in our dependent variable, which comprise 25% of our dataset. We also estimate negative binomial regressions to control for over dispersion in the dependent variable.

4. Data

Data on bilateral FCS come from OECD and UNCTAD for the period 1990-2004. The OECD reports bilateral outward FCS of 29 OECD countries in 235 host economies in millions of U.S. dollars from 1982 to 2003. Data from UNCTAD covers 29 source countries in 190 host countries.[6] The combination of these datasets leaves us with a total of 20,949 observations, of which one fifth come from UNCTAD.[7] FCS data were deflated using the U.S. producer price index from the IMF's *International Financial Statistics* (IFS) dataset.

Unfortunately, bilateral outward FCS disaggregated by sector is not available for most OECD countries. The U.S. Bureau of Economic Analysis (BEA) does provide data

[6] For those countries for which the UNCTAD data is reported in national currency, we transformed the figures into U.S. dollars using the end of period exchange rate, which was taken from the OECD. We then use the OECD dataset unless the observations are missing. Data for Australia for the period 1990-2000 was also taken from the UNCTAD, since OECD reports data for the fiscal year.

[7] Missing observations in our right-hand-side variables leave us with a total of 13,765 observations.

across sectors.[8] These stocks are reported on a historical cost basis in millions of U.S. dollars for ten sectors.[9]

GDP in current U.S. dollars was taken from the *World Development Indicators* (WDI) and deflated by the U.S. producer price index from IFS to get the real GDP. Our measure of skill-labor abundance is the ratio between skilled and unskilled workers which were taken from the often-used education data provided by Barro and Lee (2000).

We include two variables to account for investment costs. As a measure of the host-country political instability we follow Eichengreen and Tong year and use the Political Risk Rating from ICRG. This rating goes from 0 to 100, where higher scores indicate more political stability. To clarify the interpretation of this variable's coefficient we redefine this measure as 100 minus the index. We thus expect a negative coefficient on this variable. As a measure of economic volatility we include the volatility of the real exchange rate. We calculate this as the standard deviation of the monthly growth rate of the real exchange rate.[10]

For trade costs, we follow the KCM literature and use 100 minus the degree of openness, where openness is the ratio of merchandise imports over GDP. Merchandise imports were taken from the WTO database. Finally, the indexes on natural resources are the ratio of a country's sector net exports divided by the labor force. These data were also taken from the WDI. Tables A1 and A2 in the appendix contain the summary statistics for the resulting dataset and the list of countries in our sample.

[8] www.bea.org

[9] BEA sector classification is SIC until 1998 and NAICS since 1999. However, total stocks in the manufacturing sector are comparable across classifications.

[10] We calculate the RER as the product of the U.S producer price index and the market exchange rate, divided by the consumer price index. These data were taken from the International Monetary Fund's International Financial Statistics database.

5. Results

Before reporting the KCM results, Table 1 provides estimates of unconditional substitution (complementarity) elasticities. That is, the results come from a model conditioned only on time effects and country-pair fixed effects.[11] We present results based on both the aggregate and sector FCS data. The point estimates of China's and India's effect on LAC are reported at the bottom of the table. The first panel reports the unconditional effect of China and India on aggregate FCS. Column 1 shows the results of the OLS estimation. The impact of China is positive and significant for the rest of the world, and LAC does not appear to be statistically different. The coefficient on the Indian FCS variable also appears with a positive sign and is statistically different from zero. The effect on LAC is not statistically different either, but the corresponding point estimate is positive.

The second column shows the Poisson regression results. We use the Poisson conditional-mean estimator to control for country-pair fixed effects proposed by Hausman et al. (1984). The results are qualitatively similar to those of the OLS estimation, although the magnitudes of the impact of China and India are considerably smaller. We continue to find that China and India have a positive effect on the rest of the world, and the effect on LAC is not different. The overall effects of China and India on LAC are 0.22 and 0.19 respectively, which are about half of the corresponding OLS estimate. The third column shows the estimates for the Negative Binomial conditional-mean estimator also proposed by Hausman et al. (1984). Again, we find that China and India have had a positive effect on FCS in the world and LAC. In brief, the unconditional

[11] For the sake of brevity, we do not report unconditional partial correlations without time or country-pair fixed effects.

estimators show a positive partial correlation between FCS in China and India and those in the rest of the world.

The second panel of the table shows the results using the U.S. sector data. As with the OECD and UNCTAD data, there is an unconditional positive correlation between Chinese FCS and FCS in LAC in the U.S. data. In contrast, here we cannot reject the hypothesis that the overall impact of India FCS in LAC is different from zero. These results are robust to the use of the alternative estimators. The impact of China in the manufacturing sector also appears to be either positive or not significant. The evidence of the impact of India in the manufacturing sector is somewhat mixed. Indian FCS in the manufacturing sector has a negative and significant coefficient in the Poisson estimation. However, this finding is not robust across estimators. We find no effect of this variable using the OLS and an overall positive effect using the Negative Binomial estimator.

Table 2 reports the results from the fully specified KCM, based on the OECD and UNCTAD data. Again, the bottom panel contains the point estimates of the China and India effects on LAC FCS. The first column shows the OLS results for our benchmark model. The results for most of the control variables are similar to those in the KCM literature and consistent with the theory. GDPSUM and GDPDIF have the expected signs and are statistically significant. The coefficient in the skill difference is negative, which is contrary to the theory but consistent with other empirical findings (e.g., Blonigen et al 2003). We do not find a different effect for the negative skill difference. Both measures of investment cost are negative and statistically significant. The distance and the trade costs variables also have a negative coefficient and are statistically different from zero.

The estimates of the impact of Chinese and Indian FCS on other countries FCS do not show evidence of FCS substitution. The coefficient on China's FCS is not different from zero, and the interaction with the Latin American is positive, suggesting that FCS in China and LAC are complements. As shown in the bottom of the table, the overall effect of China on LAC is 0.26 and statistically different from zero. Indian FCS has a positive effect on FCS for the world average, and that effect is not different for LAC. Again, the overall effect in LAC is positive and significant.

Columns 2 and 3 in Table 2 present results from Poisson and Negative Binomial estimators. The estimates of the control variables are consistent with the OLS coefficients. The coefficients on China FCS, although a bit bigger, are also similar to those in the OLS regressions. The difference appears in the estimates for India. The Poisson estimator produced a significantly negative coefficient on the Indian FCS multiplied with the LAC dummy, thus making the overall effect of Indian on LAC FCS negative. The Negative Binomial estimator also shows that the effect of Indian FCS is different in LAC than in the rest of the world, although here we cannot reject the hypothesis that the overall effect on LAC is zero.

One potential weakness of the aforementioned specifications reported in Table 2 is that they do not control for global trends affecting FDI in China and India as well as in other developing countries. Also, estimates on the variables may be biased due to unobserved time-invariant country-pair characteristics.

The second panel in Table 2 reports the results from specification that control for time effects and country-pair fixed effects. The KCM performs well, especially with the count data estimators. Nonetheless, the coefficients on lGDPsum and lGDPdifsq are smaller once we include the fixed effects and no longer significant in the OLS estimation.[12] The first columns in the second panel shows that even after controlling for time effects, the average impact of FCS in China and India are positive in the OLS estimation. The effect on LAC is not statistically different, but remains positive and significant.

Columns 6 and 7 show the Poisson and Negative Binomial results, using the conditional mean estimators. The estimates on the effects of China and India are consistent with those in the OLS. The impact of China and India on the rest of the world's FCS is positive and significant, and it is not different for LAC.

The bottom panel of the table presents the fixed-effects results that also control for natural resource abundance in the host countries. The coefficients on these latter variables are not different from zero. Only in the Poisson model the fuel abundance variable appears significant and has a negative sign, indicating that abundance of fuel resources is negative correlated with FCS. The estimates of the Chinese and Indian variables remain unchanged, however.

One concern about these results is related to the data, which might underestimate China's FCS. Hong Kong has been a part of China since 1997 and therefore should be considered part of the Chinese economy. Moreover, some observers have argued that China's and Hong Kong's trade data should be combined to approximate the trade flows coming from China mainland due to transshipments of merchandise through Hong Kong (Fernald et al. 1998). Hong Kong has a significant contribution in the marketing and distribution of Chinese exports, thus making it difficult to differentiate the value added in each country. Similarly, multinational enterprises may be moving to Hong Kong to

[12] We include the time effects and the fixed effects one at a time. The comparison of these results indicates the fixed effects are driving these results.

conduct activities in mainland China. Also, FDI from third countries may be channeled through Hong Kong even prior to 1997 (Fung 1997).

To deal with these potential issues, we summed China and Hong Kong FCS and repeated the econometric analyses. The results remain unchanged and for the sake of brevity are not reported here.[13] There is still no evidence of a substitution effect between China-Hong Kong and other countries, including LAC, and there is some evidence of complementarities.

In spite of this evidence, there is still the possibility that the emergence of China and India may have taken foreign investment in some sectors from other developing economies. Cravino, Lederman, and Olarreaga (2006) highlighted trends in FCS in the manufacturing sector in China, India, and Latin America that may differ from trends in aggregate FCS. As a robustness check, the following section thus discusses results based on U.S. foreign investment data across industries.

5.1. U.S. foreign investment across sectors

To deal with the potential heterogeneity across sectors, with an emphasis on manufacturing industries, here we repeat the analysis using U.S. sector FCS data. Our benchmark specification is again the KCM in logs. We include all the previously discussed explanatory variables, and also an interaction of all these variables with a dummy for the manufacturing sector. Again, we include time dummies and fixed effects in the estimations.[14]

[13] These results are available from the authors upon request.

[14] In the conditional-mean Negative Binomial specification we also include a dummy for the manufacturing sector. This is possible because the Conditional Mean estimator proposed by Hausman, Hall, and Griliches (1984) does not control for all stable covariates -- see Alison and Waterman (2002).

The use of the U.S. data makes it impossible to estimate the effect of distance and source country trade costs together with time and host country effects, since the U.S. appears as the only source country in this sample. Also, since the U.S. is more skilled labor abundant than any other country in the dataset, there is no need to take the absolute value of the skill difference between the source and host countries. The results for these estimates are reported in Table 3, where the bottom panel of the tables shows the point estimates of the effects of Chinese and Indian FCS on LAC FCS.

The first column of the table shows the OLS estimation. Again, we do not find any evidence of substitution in these estimations. Although none of the variables of interest are statistically different from zero, the overall coefficient of the effect of China on LAC is positive and significant, which is consistent with our previous estimates. The overall coefficient for India is also positive, but not significantly different from zero. There is no evidence of an impact of China on U.S. FCS in other countries manufacturing industries. The overall coefficient for India on the other hand is 0.33 and significant at the 10 percent level.

The second column of Table 3 shows the Poisson estimates. As in the OLS estimation, the overall impact of China on LAC continues to be positive and significant and the overall impact of India on LAC is not different from zero. The impact of China in the manufacturing sector is also continues to be positive. Finally, the negative coefficient of the impact of China in LAC manufacturing is no longer significant once we control for the KCM variables, thus shedding more doubts on the substitution hypothesis.

The last column shows the results of the Negative Binomial estimator. The signs of the coefficients for the aggregate effect of China and India are consistent with the other estimators. However, as in the OLS estimation, we cannot reject the hypothesis that the impact of China in LAC manufacturing FCS is zero. The impact of India continues to be non significant.

As a robustness check, we repeated the sector analysis by using the sum of China's (mainland) and Hong Kong's FCS instead of China alone as the proxy for the effects from China. The results remain virtually unchanged. We continue to find that there is no substitution effect between FCS in China and India and those in LAC in the manufacturing sector. [15]

In sum, using U.S. data we continue to find that the impact of China has been positive for LAC FCS but not necessarily for other economies. This was not the case in the manufacturing sector, where we found that China had no impact at all. In contrast, we do not find an overall impact from India with these data. The evidence in the manufacturing sector is less clear, although our preferred Negative Binomial estimator yielded a positive effect of India on LAC FCS in manufacturing activities.

5.2. Accounting for heterogeneity within LAC

It is possible that China and India have had different effects across LAC countries. For example, China may be having a negative impact in those countries where assembly operations (the so-called *maquilas*) are important, but not in other countries. We therefore divide LAC countries into three sub regions roughly according to their production structure. These sub regions are Central America and Mexico where *maquilas* are commonplace, Andean countries that tend to export a combination of agricultural and

[15] These results are available from the authors upon request.

labor-intensive products as well as petroleum, and the Southern Cone countries that have vast natural resources, especially arable land. [16]

The results are reported in Table 4. For the sake of brevity, we only report the coefficients of our variables. The first panel of the table shows the estimates using the bilateral data from OECD and UNCTAD. We find that the results for the three sub regions are similar to those of LAC as a whole. That is, we do not find a negative effect of either China or India in any of the sub regions, and there is still evidence of complementarities. It is noteworthy that the impact of China is larger on the Central American and Andean countries, whereas India has a larger effect on the Southern Cone.

The second panel of the table reports estimates of the impact of China and India on total U.S. stocks in the three sub regions. We continue to find no evidence of substitution effects. The positive effect for LAC as a whole, however, is only significant for the Southern Cone. The overall effect of India on U.S. stocks continues to be zero for all sub regions.

Finally, the last panel of table 4 reports the impact of China and India in FCS in the manufacturing sector. We find that there is heterogeneity across sub regions in this sector. The overall coefficient of China in the manufacturing sector is negative for Central America in the OLS specification, suggesting that China may be diverting manufacturing FCS away from this region. However, this finding is not robust to the use of the Poisson and Negative Binomial estimators. There is no evidence that growing FCS in China have had a negative impact on the FCS of the other two regions. The results for India are in general not significant and do not differ much across sub regions. In contrast,

[16] Central American Countries: Costa Rica, Dominican Republic, El Salvador, Guatemala, Haiti, Honduras, Jamaica, Mexico, Nicaragua, Panama and Trinidad and Tobago. Andean Countries: Bolivia, Colombia, Ecuador, Peru and Venezuela. Southern Cone Countries: Argentina, Brazil, Chile, Paraguay and Uruguay.

the Poisson estimator has a negative coefficient, but this result is not robust as it is not present with the alternative estimators.

In brief, the conclusions drawn from previous sections apply across LAC sub regions. The results for the aggregate bilateral stocks from the OECD do not show much variation across regions within LAC, and strongly support the complementarity hypothesis. The overall effects of China and India are less important in the U.S. data, and the positive effect of China found for LAC in section 5.1 is mainly due to its positive effect in the Southern Cone countries' FCS. Differences across sub regions come out in the manufacturing sector data, where there is surprisingly weak evidence that China and India might have had negative effects on Central America and the Southern Cone respectively, as these results are not robust across estimators.

6. Conclusions

In this paper, we empirically estimate the impact of China and India on foreign investment in other economies, with special emphasis on LAC. Using bilateral outward stocks data from UNCTAD and OECD, we find that China and India had a positive effect on the FCS in LAC and the rest of the world. This result is robust to the use of Poisson and Negative Binomial estimators, and to the inclusion of time dummies and fixed effects. The evidence based on U.S. foreign investment data across industries also suggests that the effect of China has been positive on aggregate for all sectors, but there is little evidence that this is the case in the manufacturing sector. It is worth mentioning that there is some evidence of a negative effect in Central American countries, although this evidence is not confirmed by the count data estimators. In contrast, India appears to have had no impact on LAC FCS from the U.S. We do find some evidence of Indian substitution effects in the manufacturing sector when we concentrate on the Southern Cone countries, but this finding is not robust to the use of the Negative Binomial estimator.

The preponderance of the evidence thus suggests that the emergence of China and India in the global economy has had positive effects on global FDI flows. Fears of a global competition for FDI consequently seem misplaced in light of the data. Policymakers concerned about attracting foreign investors into their economies should thus focus their efforts on the fundamental determinants of FDI. The KCM model seems to be broadly supported by the global data, and is thus useful for thinking about policies that will attract FDI, including trade reforms, dealing with macroeconomic volatility, and other pro-growth reforms.

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	Table 1: Unconditional Coefficients					
	Aggregate Regressions. OECD and UNCTAD Data			**Sector Regressions. U.S. Data**		
	Logs	**Poisson**	**NEG.BIN.**	**Logs**	**Poisson**	**NEG.BIN.**
lStocksChina	0.40	0.31	0.16	0.01	0.07	0.01
	[10.98]**	[4.74]**	[7.55]**	[1.08]	[2.71]**	[0.77]
lStocksChina_LAC	0.00	-0.09	-0.02	0.03	0.08	0.05
	[0.04]	[1.50]	[0.58]	[1.70]	[1.16]	[1.85]
lStocksIndia	0.38	0.08	0.07	0.04	0.06	0.05
	[10.19]**	[2.87]**	[3.61]**	[2.64]**	[1.87]	[2.80]**
lStocksIndia_LAC	0.02	0.11	0.00	-0.04	-0.08	-0.03
	[0.23]	[1.43]	[0.07]	[1.56]	[1.65]	[1.10]
lStocksChina_man				-0.07	0.04	-0.04
				[0.76]	[0.69]	[0.58]
lStocksChina_LAC_man				-0.03	0.10	-0.05
				[0.29]	[0.77]	[0.60]
lStocksIndia_man				0.06	-0.41	0.21
				[0.35]	[2.57]*	[2.07]*
lStocksIndia_LAC_man				0.19	-0.30	0.03
				[0.85]	[0.93]	[0.22]
Observations	11363	10651	10651	6690	4971	4971
Number of group(country pairs)	1486	1128	1128	873	603	603

Robust t statistics in brackets

* significant at 5%; ** significant at 1%

China's effect on LAC	0.41	0.22	0.14	0.05	0.15	0.06
India's effect on LAC	0.40	0.19	0.07	0.00	-0.01	0.02
China's effect on LAC manufacturing	N.A.	N.A.	N.A.	-0.06	0.29	-0.03
India's effect on LAC manufacturing	N.A.	N.A.	N.A.	0.25	-0.72	0.25
p-value test: China's effect on LAC=0	0	0	0	0.01	0.02	0.01
p-value test: India's effect on LAC=0	0	0.01	0.04	0.89	0.67	0.44
p-value test: China effect in LAC manufacturing=0	N.A.	N.A.	N.A.	0.51	0.00	0.72
p-value test: India effect in LAC manufacturing=0	N.A.	N.A.	N.A.	0.20	0.03	0.01

Table 2: Estimations of the KCM with China and India effects

	Including China and India			Fixed and time effects			Fixed effects, Time Effects and Endowments		
	Logs	Poisson	NEG.BIN.	Logs	Poisson	NEG.BIN.	Logs	Poisson	NEG.BIN.
lGDPsumij	1.99	2.00	1.66	-0.19	0.77	0.52	-0.10	0.75	0.58
	[14.09]**	[15.40]**	[12.08]**	[0.71]	[3.78]**	[6.43]**	[0.37]	[3.35]**	[7.76]**
lGDPdifsqij	-0.35	-0.22	-0.24	0.01	-0.08	-0.06	0.00	-0.08	-0.07
	[8.31]**	[5.87]**	[5.15]**	[0.39]	[2.16]*	[3.38]**	[0.06]	[2.19]*	[4.75]**
laskdifij	-0.20	-0.05	-0.16	0.18	0.01	-0.10	0.14	0.01	-0.06
	[2.49]*	[0.59]	[1.85]	[1.62]	[0.05]	[2.03]*	[1.44]	[0.06]	[1.17]
laskdif_negij	0.00	-0.03	-0.06	-0.04	0.07	0.04	-0.01	0.08	0.03
	[0.03]	[0.27]	[0.39]	[0.94]	[1.69]	[1.17]	[0.24]	[1.89]	[0.80]
volrerj	-4.93	-19.67	-1.00	-1.79	-1.54	-1.89	-2.61	-1.61	-1.81
	[5.19]**	[2.39]*	[0.90]	[2.51]*	[3.10]**	[4.08]**	[2.97]**	[3.27]**	[2.99]**
linv_costj	-1.62	-1.20	-1.28	-0.20	-0.19	-0.43	-0.15	-0.19	-0.37
	[11.65]**	[9.42]**	[11.31]**	[1.99]*	[4.87]**	[8.24]**	[1.50]	[4.36]**	[7.00]**
lT_costi	-1.26	-1.42	-1.06	-0.26	-0.67	-1.54	-0.22	-0.72	-1.43
	[2.93]**	[3.56]**	[2.90]**	[0.36]	[1.03]	[5.64]**	[0.28]	[1.13]	[5.77]**
lT_costj	-0.29	-0.09	-0.17	-0.91	-0.41	-0.13	-0.82	-0.37	-0.12
	[6.75]**	[2.41]*	[5.12]**	[3.87]**	[1.32]	[4.40]**	[3.23]**	[1.48]	[3.61]**
ldist	-0.88	-0.57	-0.49						
	[11.49]**	[8.15]**	[7.73]**						
lStocksChina	0.03	-0.06	0.08	0.40	0.28	0.13	0.41	0.28	0.15
	[0.86]	[0.69]	[2.69]**	[10.83]**	[5.34]**	[5.73]**	[10.61]**	[4.89]**	[6.43]**
lStocksChina_LAC	0.23	0.45	0.31	0.01	-0.08	0.02	-0.03	-0.07	0.00
	[2.66]**	[4.04]**	[3.77]**	[0.20]	[1.43]	[0.65]	[0.48]	[1.34]	[0.11]
lStocksIndia	0.44	0.24	0.18	0.38	0.08	0.07	0.38	0.09	0.08
	[11.82]**	[2.61]**	[6.81]**	[10.12]**	[3.29]**	[4.20]**	[9.72]**	[3.82]**	[4.90]**
lStocksIndia_LAC	-0.18	-0.59	-0.26	0.03	0.13	-0.01	0.07	0.17	-0.01
	[1.84]	[4.31]**	[2.93]**	[0.36]	[1.71]	[0.33]	[0.81]	[1.74]	[0.17]
Natural Resources: Agriculture							-0.0001	0.0001	0.0001
							[0.84]	[0.66]	[1.12]
Natural Resources: Fuel							0.0000	-0.0001	0.0000
							[0.55]	[2.16]*	[1.33]
Natural Resources: Mining							0.0002	0.0000	0.0000
							[0.79]	[0.10]	[0.23]
Observations	11363	11363	11363	11363	10651	10651	9782	9295	9295
Number of group(country pairs)	1486	1486	1486	1486	1128	1128	1311	1055	1055
p-value likelihood ratio test alpha=0			0.000						

Robust t statistics in brackets (clusters pairid), bootstrap t-statistics in Poisson and Negative Binomial with fixed effects

* significant at 5%; ** significant at 1%

China's effect on LAC	0.26	0.39	0.40	0.42	0.21	0.15	0.38	0.20	0.14
India's effect on LAC	0.25	-0.35	-0.08	0.40	0.21	0.06	0.45	0.26	0.07
p-value test: China's effect on LAC=0	0	0	0	0	0	0	0	0	0.06
p-value test: India's effect on LAC=0	0.01	0	0.36	0	0	0.07	0	0	0

Table 3: Sector Regressions			
	Fixed effect, Time Effects		
	OLS	Poisson	NEG. BIN.
lGDPsum	19.03	8.16	12.06
	[6.17]**	[2.02]*	[3.18]**
lGDPsum_man	1.18	-0.16	1.39
	[1.08]	[0.10]	[1.35]
lGDPdifsq	2.81	1.34	2.06
	[6.04]**	[1.82]	[1.68]
lGDPdifsq_man	-0.55	-0.89	-0.73
	[2.58]**	[1.37]	[1.85]
lskdif	0.39	-1.42	0.06
	[0.32]	[0.51]	[0.32]
lskdif_man	-0.87	0.45	-0.14
	[0.62]	[0.15]	[0.29]
(mean) volrer	-0.90	-0.95	-1.81
	[1.77]	[0.78]	[2.14]*
volrer_man	0.55	0.05	1.22
	[0.40]	[0.03]	[0.85]
linv_cost	-0.12	-0.04	-0.12
	[1.11]	[0.26]	[0.82]
linv_cost_man	-0.09	0.05	-0.19
	[0.54]	[0.28]	[0.85]
lT_cost2	-0.77	0.41	-0.12
	[4.29]**	[0.78]	[1.53]
lT_cost2_man	0.42	-0.09	-0.10
	[1.29]	[0.14]	[0.52]
lStocksChina	0.02	0.07	0.01
	[1.30]	[2.64]**	[0.49]
lStocksChina_LAC	0.03	0.08	0.07
	[1.30]	[1.09]	[2.60]**
lStocksIndia	0.04	0.06	0.04
	[2.43]*	[1.64]	[2.74]**
lStocksIndia_LAC	-0.03	-0.07	-0.01
	[1.27]	[1.40]	[0.38]
lStocksChina_man	-0.05	0.20	0.00
	[0.47]	[1.75]	[0.03]
lStocksChina_LAC_man	-0.09	-0.01	-0.10
	[0.72]	[0.05]	[1.11]
lStocksIndia_man	0.06	-0.14	0.03
	[0.25]	[0.66]	[0.18]
lStocksIndia_LAC_man	0.27	-0.20	0.12
	[1.16]	[0.78]	[0.87]
Observations	6690	4971	4971
Number of group(wbcode2 sector)	873	603	603

Robust t statistics in brackets

* significant at 5%; ** significant at 1%

Table 3: Cont.			
China's Effect on LAC	0.04	0.15	0.08
India's Effect on LAC	0.01	-0.01	0.03
China's Effect on LAC manufacturing	-0.10	0.34	-0.02
India's Effect on LAC manufacturing	0.33	-0.35	0.18
p-value test: China effect in LAC=0	0.02	0.03	0.00
p-value test: India effect in LAC=0	0.74	0.76	0.26
p-value test: China effect in LAC manufacturing=0	0.43	0.01	0.81
p-value test: India effect in LAC manufacturing=0	0.16	0.26	0.35

Table 4: China and India Effects across LAC Sub Regions

	Aggregate Data			U.S. Data			U.S. Data: Manufacturing		
	OLS	Poisson	Neg. Bin.	OLS	Poisson	Neg. Bin.	OLS	Poisson	Neg. Bin.
China's Effect in Central American Countries	0.45	0.22	0.13	0.02	0.20	0.05	-0.33	0.27	-0.06
	[0.00]**	[0.06]*	[0.02]**	[0.47]	[0.31]	[0.14]	[0.03]**	[0.29]	[0.56]
India's Effect in Central American Countries	0.34	0.18	0.02	0.01	-0.01	0.01	0.86	-0.10	0.16
	[0.01]**	[0.45]	[0.70]	[0.64]	[0.83]	[0.83]	[0.00]**	[0.89]	[0.46]
China's Effect on Andean Countries	0.48	0.29	0.18	0.03	0.11	0.13	0.07	0.37	-0.01
	[0.00]**	[0.02]**	[0.00]**	[0.40]	[0.15]	[0.02]**	[0.73]	[0.59]	[0.94]
India's Effect on Andean Countries	0.35	0.19	0.04	-0.02	-0.01	0.00	-0.03	-0.35	0.17
	[0.00]**	[0.06]*	[0.58]	[0.77]	[0.78]	[0.97]	[0.94]	[0.26]	[0.60]
China's Effect in Southern Cone's Countries	0.24	0.20	0.15	0.08	0.09	0.09	0.24	0.43	0.09
	[0.02]**	[0.01]**	[0.00]**	[0.00]**	[0.02]**	[0.03]**	[0.12]	[0.01]**	[0.63]
India's Effect in Southern Cone's Countries	0.59	0.28	0.15	-0.02	0.01	0.07	-0.37	-0.58	0.07
	[0.00]**	[0.02]**	[0.00]**	[0.60]	[0.90]	[0.17]	[0.13]	[0.05]*	[0.78]
Observations	9782	9295	9295	6690	4971	4971	6690	4971	4971
Number of Groups	1311	1055	1055	873	603	603	873	603	603

p-values in brackets correspond to the F-test of the null hypothesis that the effect = 0. All estimates come from estimations of the fully specified CKM, but other parameter estimates are not reported. * significant at 5%; ** significant at 1%.

Table A.1: Summary Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
FDIstock	13765	3379.089	15004.25	0	322733.4
GDPsum	13765	2090.304	2772.533	12.61177	14743.19
GDPdifsq	13765	9708931	2.45E+07	0.0114306	1.11E+08
askdif	13765	1.000673	0.65493	0.0000104	2.702084
volrer	13765	0.025836	0.034664	0.0022654	0.621135
inv_cost	13765	28.71217	13.18151	3	87
T_cost1	13765	74.8935	10.90686	7.473358	95.12417
T_cost2	13765	68.83891	20.26945	0.1	97.11642
dist	13765	3935.745	2576.506	137.2279	12272.34
StocksChina	12666	1764.356	3186.026	0.098907	22096.84
StocksIndia	12173	514.8716	866.7437	0.0960905	5613.682

Table A.2: Countries Included in the Aggregate-Data Regressions

Source countries	LAC host countries	Other host countries	
Australia	Argentina	Algeria	Malawi
Austria	Bolivia	Austria	Malaysia
Belgium	Brazil	Bahrain	Mali
Brazil	Chile	Bangladesh	Moldova
Bulgaria	Colombia	Belgium	Mozambique
Canada	Costa Rica	Botswana	Netherlands
Colombia	Dominican Republic	Bulgaria	Niger
Denmark	Ecuador	Cameroon	Norway
Estonia	El Salvador	Canada	Pakistan
Finland	Guatemala	Congo, Dem. Rep.	Philippines
France	Guyana	Congo, Rep.	Poland
Germany	Haiti	Denmark	Portugal
Greece	Honduras	Egypt, Arab Rep.	Romania
Hungary	Jamaica	Estonia	Russian Federation
Iceland	Mexico	Finland	Senegal
Ireland	Nicaragua	France	Sierra Leone
Italy	Panama	Gambia, The	Singapore
Japan	Paraguay	Germany	South Africa
Kazakhstan	Trinidad and Tobago	Ghana	Spain
Korea, Rep.	Uruguay	Greece	Sri Lanka
Mexico	Venezuela, RB	Guinea-Bissau	Sudan
Netherlands		Hong Kong, China	Sweden
New Zealand		Hungary	Switzerland
Norway		Indonesia	Syrian Arab Republic
Poland		Iran, Islamic Rep.	Taiwan, China
Portugal		Ireland	Tanzania
Spain		Israel	Thailand
Sweden		Italy	Togo
Switzerland		Japan	Tunisia
Turkey		Jordan	Turkey
United Kingdom		Kazakhstan	Uganda
United States		Kenya	United Kingdom
		Korea, Rep.	United States
		Kuwait	Vietnam
		Latvia	Yemen, Rep.
		Liberia	Zambia
			Zimbabwe